Active Vibration Suppression Using Neural Networks

Yong Xia, and Ahmad Ghasempoor

***Abstract*—Vibration detection and control strategies strive to reduce the effect of harmful vibrations on machinery and people. In general, vibration control strategies are classified as passive or active. While passive vibration control techniques are generally less complex, there are more limits to their effectiveness. Active vibration control strategies, on the other hand, can be very effective but require more complex algorithms and are especially susceptible to time delays. This paper introduces an active and adaptive vibration control system which, based on using neural network and newest digital signal processing techniques, automatically detects noisy sinusoidal vibration parameters of a cantilever beam and generates control signals to an actuator to cancel the vibration. The control signal is generated based on calculations of a neural network and real-time digital processing. The system can repeat the vibration detection and control loop in every 25 ms, and the newest control signal is added to the original one to minimize the beam vibration. The system has been evaluated experimentally and the results showed its validity.**

***Index Terms*—Active vibration control, adaptive, artificial neural networks, real-time digital signal processing**

I. INTRODUCTION

Vibration control is the effort to reduce the negative consequences of vibration effectively. Two main groups of vibration control methods are passive and active methods. Passive vibration control methods include elimination of additional energy sources, eliminating or decreasing input forces and isolation from external disturbances [1]. The passive vibration control methods have limitations including ineffectiveness in low frequency range, lack of robustness, and increased size and weight of the system. Active vibration control (AVC) methods, on the other hand, work by providing an additional energy supply to the vibration systems, and alleviate the problems of contradictory requirements imposed on passive vibration control techniques.

The research in AVC has been expanding since 1930s, and especially rapidly in the past three decades. AVC is achieved by using a control source to introduce a secondary disturbance into a system to cancel the existing disturbance, thus resulting in an attenuation of the original vibration. These secondary sources are interconnected through an electronic system using a specific signal processing algorithm for a particular cancellation scheme. Even though the concept is simple, it is only with the development of low-cost fast digital signal processing (DSP) systems during the last 20 years that the implementation of practical active vibration control systems has become feasible. The continuous progress of AVC includes the development of improved adaptive signal processing algorithms, transducers, and DSP hardware.

The objective of the current work is to develop an effective adaptable AVC system to suppress the noisy sinusoidal vibration of a cantilever beam, which is familiar in machining chatter. The system should be a simple to implement, noise tolerant, and robust real-time online AVC system.

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II. METHODOLOGY

A. Vibration Detection

The cantilever beam vibration here includes noisy sinusoidal signals.

Different methods for detecting sinusoid parameters can be found in [2]. Classical methods include the maximization of periodogram (MP) and the minimization of the sum of squared error by non-linear least squares (NLS) regression. In [3], an algebraic approach is proposed for the fast and reliable, on line, identification of the amplitude, frequency and phase parameters in unknown noisy sinusoidal signals.

Generally, the algebraic method uses the algebraic derivative method in the frequency domain yielding exact formulae, when placed in the time domain, for the unknown parameters. Considering an uncertain sinusoidal signal of the form:

$$x(t) = A\sin(\omega t + \phi) + K \tag{1}$$

where A is the unknown amplitude, ω is the unknown frequency, ϕ is the unknown phase, and K is an unknown constant bias perturbation term, the Laplace transform of this signal is given by [3]:

$$x(s) = \frac{A\omega\cos\phi}{s^2+\omega^2} + \frac{sA\sin\phi}{s^2+\omega^2} + \frac{K}{s} \tag{2}$$

where s is the complex frequency. After many differentiations, integrations, and integral convolutions, the unknown A, ω, and ϕ can be obtained. Together with using filters, the algebraic method can deal with noise very well.

Since the algebraic approach is fast (can be performed in a quite small time interval which is only a small fraction of the first full cycle of the measured sinusoid signal), robust with respect to signal measurement noises and able to do the computation of amplitudes, frequencies and phases of a linear combination of sinusoids [3], it is utilized in the current

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work. To get more accurate parameters, especially for frequency, the outcomes of the algebraic approach are applied to classic methods, which require extremely precise initial values to ensure convergence.

B. General Vibration Control Strategy

The general proposed AVC strategy utilized in the current work is shown in Fig. 1. In this strategy, a vibration suppression module relies on the availability of detected vibration parameters from the vibration detection module to generate control signals, i.e., *x(u)*, which are applied to the plant by secondary sources, i.e., actuators, to suppress the vibration. In Fig. 1, *x(p)* represents the primary disturbance. The plant output, i.e., *Y* in Fig. 1, is the vibration response of the plant measured at the location of interest.

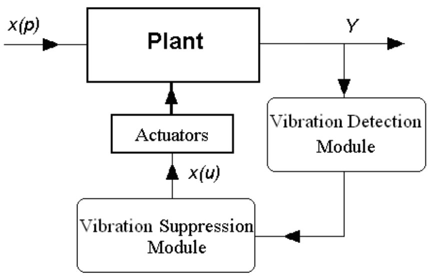

Fig. 1: The general AVC strategy

In this strategy, the following relation exists:

$$Y = F(x(p), x(u), t) \tag{3}$$

The vibration suppression module's task is to synthesize *x(u)* such that it minimizes *Y*. If a comprehensive physical model of plant is available, the control signal to the actuator, i.e., *x(u)*, could be determined through an optimization method in order to minimize Y. One such optimization method is steepest decent, where:

$$x(u)^{k+1} = x(u)^k - \alpha^k \frac{\partial Y^k}{\partial x(u)^k} \tag{4}$$

Here $\frac{\partial Y^k}{\partial x(u)^k}$ is the gradient of the dynamic model of the plant Y; $x(u)^k$ and $x(u)^{k+1}$ are the values of the control signal in the *k* and *k+1* iterations respectively; and α is the size of the steps in the direction of minimization.

The calculation of the gradient requires the availability of a differentiable physical model. However, comprehensive, differentiable physical models of complex systems usually do not exist. In this paper, a vibration suppression module is used to generate a control signal to suppress the original vibration at the location of interest. The ideal generated control vibration should have the same amplitude and frequency of the original one at that location but with a 180-degree phase difference.

C. Vibration Suppression Subsystem Design

The vibration suppression module is the most critical part of this control system. Fig. 2 shows some details of the proposed vibration suppression subsystem design.

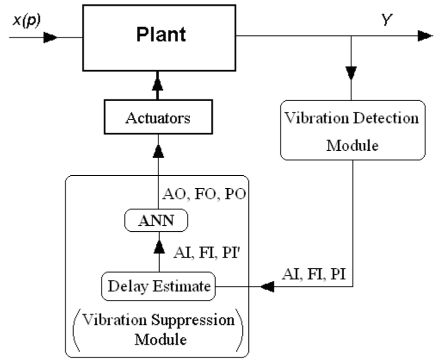

Fig. 2: Some details of the vibration suppression module

To generate an "opposite" vibration at the location of interest to suppress the original one, an ANN is utilized as an identification model of the plant based on the function approximation capability of ANNs. To make the proposed AVC system robust, the ANN model should be used for a relatively stable part of the plant. To generate control signals, the ANN model should work as an inverse model, which means the inputs of the ANN model are actually the outputs of the plant, i.e., the parameters of the vibration signal, which include amplitude (*AI*), frequency (*FI*) and phase (*PI*), while the outputs of the ANN are the parameters of the control signal, which include amplitude (*AO*), frequency (*FO*) and phase (*PO*).

Time delay in AVC is very critical. To satisfy causality of different iterations, the time delay between the iteration to collect vibration signal parameters and the iteration to send out control signal should be considered to get the actual phase input (*PI'*) to the ANN.

Thanks to the newest real-time digital signal processing techniques, signals can be collect or sent out really continuously. Real-time digital signal processing provides precise and predictable timing characteristics. Because of the deterministic property of a real-time system, the accuracy of running time of a control iteration, or a while loop, can be expected. In the current work, if the running time for each iteration is *t*, considering the time delay of one control iteration and the 180-degree phase difference, the actual phase input (PI' in Fig. 2) of the ANN model should be,

$$PI' = PI + 180 + (FI \times t - \text{int}(FI \times t)) \times 360 \tag{5}$$

D. Design of the Inverse ANN Model

As mentioned before, in the proposed AVC system, the ANN is used for function approximation and works as an inverse identification model of a part of the plant. The design of the ANN model is based on the applied AVC strategy and the actual experimental setup. Generally, design steps are as follows [4]: First, training data for the ANN models are collected via experiments according to the AVC strategy presented in the last sections; Then, the training data are analyzed in order to choose a proper normalization method; The general network architectures of the ANN models are then designed and the suitable learning algorithm is chosen; Finally, the ANN models are trained to avoid overfitting. The network architectures may be modified for better function approximation based on experimental results.

An ANN model example based on the proposed vibration suppression subsystem design is shown in Fig. 3. In this example, a multilayer feedforward ANN is utilized. The ANN architecture used here has three inputs, one hidden layer of log-sigmoid neurons and one output layer of three log-sigmoid neurons.

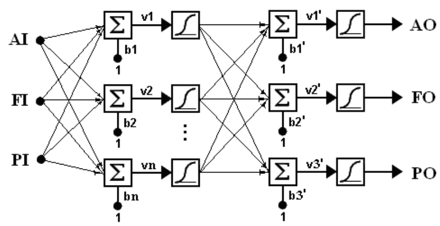

Fig. 3: ANN model example

The ideal control signal frequency (*FO*) should be the same as vibration frequency (*FI*) [5]. Moreover, the input *PI* can be cancelled if the phase difference (*PD*) between the control signal and the vibration signal is utilized (*PD = PO – PI*). In this case, the ANN can be simplified as shown in Fig. 4. In the detailed design, the number of hidden layers and the number of neurons in each hidden layers are decided by finding out what the best numbers are to obtain the smallest Mean Square Error (MSE) for validation data sets.

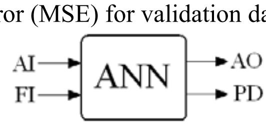

Fig. 4: Simplified ANN model

In experiments to collect training data for the ANN models, only the control actuator work to generate the plant vibration, i.e., the primary disturbance *x(p)* =0. Therefore, the inputs of the ANN are *AI* and *FO* (*FI* should be the same as *FO*). To get a robust training, which means a training affected minimally by external sources of variability, the experiments to collect training data need to be designed first. In this project, the fractional factorial design is used for the design of experiments to obtain the training data for the ANN models.

Considering the time delay between the iteration to collect vibration signal parameters and the iteration to send out control signal, the actually control signal phase should be:

$$PO = PI' - PD \tag{6}$$

where PI' can be calculated from (5) and *PI* is known in experiments.

III. Experimental Verification

Fig. 5 shows a schematic of the hardware setup developed for verification of the proposed methodology. The plant is a cantilever beam of plain carbon steel (dimensions: 550 mm x 25 mm x 4.5 mm). Two electromagnetic shakers are used to provide primary disturbance force (shaker 1) and control force (shaker 2) to the beam. These shakers are located at 150 mm and 380 mm from the clamped end, at each side of the beam respectively. To minimize the effect of the shakers on the structure, they are attached to the beam through stingers. These serve to isolate the shakers from the structure, reduce the added mass, and cause the force to be transmitted axially along the stingers. The control shaker is attached to the beam firmly; but the primary shaker simply pushes up against the beam. The resulting preload is used to maintain contact between the control shaker and the beam. The objective of the active vibration control system is to minimize the vibration of the beam at the sensor location, which is 518 mm from the clamped end of the beam.

The first natural frequency of the system was found to be around 37.7 Hz and the second natural frequency was around 135.8 Hz. Fig. 6 shows a photograph of the experimental setup as described.

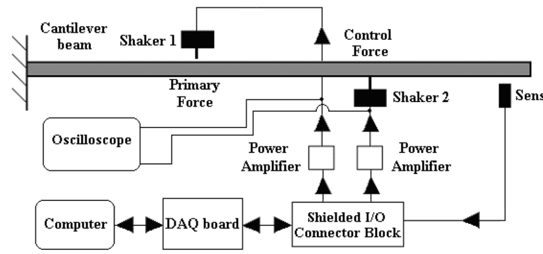

Fig. 5: Experimental setup

To evaluate the performance of the system for nonlinear vibration control problems, nonlinearity was introduced into the experimental arrangement. This could be done in two different ways. The first is by not attaching the primary shaker to the beam, but simply pushing it up against the beam. The resulting preload is used to maintain contact between the shaker and the beam. By increasing the driving force of the primary disturbance, the primary shaker rattle as it loses the contact with the beam, and therefore will make the resultant error signal spectrum noisier. The second way for introducing nonlinearity is by bandpass filtering the analog input signal from the sensor to provide a slight bias to the higher frequency harmonics, thus exaggerating the relative importance of the harmonics in the spectrum.

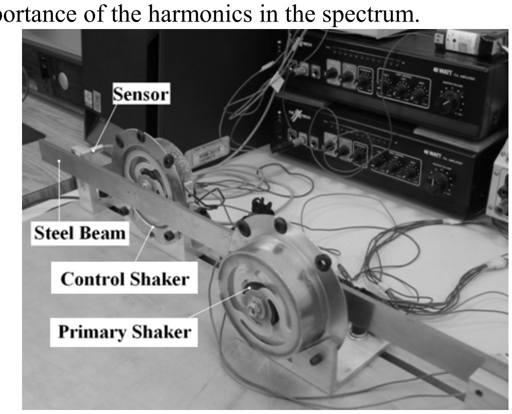

Fig. 6: Experimental setup photograph

A. AVC System Design

Based on the methodology and the experimental setup, the designed AVC system to generate a control signal is shown in Fig. 6. This control system may repeat all calculations after several control iterations and generates a new control signal for the current iteration. The new control signal obtained in the current iteration can be added to the original control signal from the beginning of the next iteration. Therefore, the actual control signal sent to the actuator is an accumulation of all generated control signals. The reason of waiting for some control iterations to generate a new control signal is to get more accurate measurements of vibration signals. A new control signal could be generated in 25 ms in experiments.

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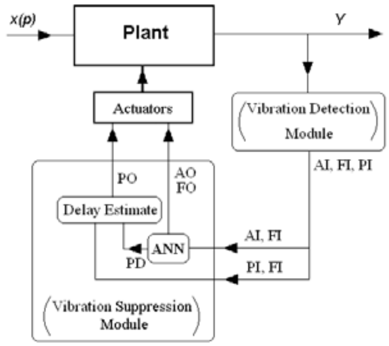


Fig. 7: The AVC system in current work

The parameters of the control signal, i.e., *AO*, *FO,* and (*PO*), can be obtained from ANN outputs and the equations in the last section. Technically, the phase difference of the control signal in programming and the actually control signal at the connector block is considered because the difference may not be the same when the system restarts.

As introduced in the last section, training data for the ANN model are collected in experiments. The data ranges are decided by the regions of interest for each variable and hardware performance limitations. Since the frequency response ranges for the two amplifiers are 20 Hz to 30 KHz, and the vibration frequency range of interest is 25 Hz to 55 Hz in the current work, the frequency range 25 Hz to 55 Hz is used for the control signal. To find out the proper amplitude ranges for the signals sent to the shakers, many experiments were undertaken. Considering the measurement range of the sensor and the hardware setup, according to the results of these experiments, the peak-to-peak amplitude range for the control signal sent to the actuator is set from 0.002 V to 0.038 V. The phase difference range can be set from 0 degree to 360 degrees.

To reduce harmful effects, e.g., the squashing effect, of using sigmoid transfer functions in the hidden layer and the output layer of the ANN model, and normalization, the above data ranges can be divided into several sub-ranges, e.g., the original frequency range can be divided into three smaller sub-ranges: 25 Hz to 35 Hz, 35 Hz to 45 Hz and 45 Hz to 55 Hz. ANN models are trained separately for different sub-ranges. Moreover, Resilient Backpropagation (RPROP) algorithm is utilized to train ANN models because, although it is not the fastest one, theoretically, it can also help to reduce squashing effect of the magnitudes of partial derivatives.

The values of all training data were normalized for efficient processing by the ANN. The data are normalized to a range of 0.1 to 0.9 by using the following equation:

$$x_{scaled} = 0.8 \times \frac{x - x_{\min}}{x_{\max} - x_{\min}} + 0.1 \qquad (7)$$

where x is the real value, x_{scaled} is the normalized value, $x_{\min}$ is the minimum value and $x_{\max}$ is the maximum value of one input or output.

The best ANN architecture found via experiments for the AVC system is like the example shown in Fig. 3. It is a multilayer feedforward ANN, which has two inputs, one hidden layer of 12 log-sigmoid neurons and one output layer of two log-sigmoid neurons. The output layer uses a log-sigmoid transfer function because the outputs of the ANNs are supposed to be constrained to a range of 0 to 1 and it is a good choice in the architecture for the current experiment setup [5]. This ANN architecture provides the smallest Mean Square Error (MSE) and has very good performance for generalization in experiments. For the same experimental setup, the ANN architecture did not change, but the weights between neurons changed for different data sub-ranges after training.

B. Experimental Results

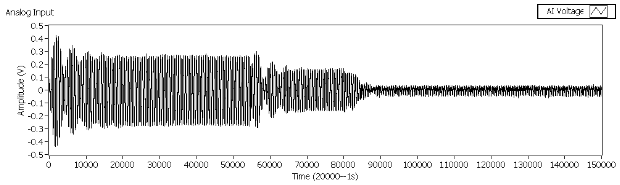
In order to evaluate the performance of the AVC system experimentally, a noisy sinusoidal signal was sent to the primary shaker to generate beam vibration. The controller was turned on several seconds after the start of the vibration to allow steady state to prevail.

All the analog input and analog output signals, and FFT (magnitude and phase) are displayed on user interfaces graphically only on a host computer and let the target computer work as a dedicated real-time system. The sampling rate for data analysis was 20000 Hz.

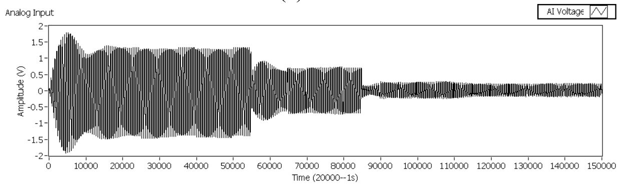
Fig. 8 shows five examples of the beam vibration at the sensor location in the first 7.5 seconds. The figures are grabbed from a user interface directly. In all the experiments, the primary shaker was driven with a primary noisy sinusoidal signal from the beginning. After about 2.75 seconds, a control signal was generated and sent to the control shaker, but with only about a fraction, e.g., around 70%, of the calculated amplitude to get some vibration remained for a second control signal to check out the adaptability of the AVC. Then, after about 1.5 seconds a new control signal was generated based on the current vibration status and added to the original control signal sent to the control shaker.

In Fig. 8(a), for the primary signal, the frequency is about 32.33Hz, the amplitude is about 0.038V, and the signal-to-noise ratio (SNR) is about 40; In Fig. 8(b), for the primary signal, the frequency is about 38.38Hz, which is close to the first natural frequency, the amplitude is about 0.028V, and the SNR is about 40; In Fig. 8(c), for the primary signal, the frequency is about 43.58Hz, the amplitude is about 0.070V, and the SNR is about 35; In Fig. 8(d), for the primary signal, the frequency is about 33.07Hz, the amplitude is about 0.099V, and the SNR is about 38; In Fig. 8(e), for the primary signal, the frequency is about 28.88Hz, the amplitude is about 0.059V, and the SNR is about 35.

Fig. 8(a) shows that the amplitude of the vibration was reduced from about 0.58V (peak to peak) to about 0.1V, which represents about 82.7% reduction of the beam vibration at the sensor location; Fig. 8(b) shows that the amplitude of the vibration was reduced from about 2.88V to about 0.5V, which represents about 82.6% reduction of the beam vibration at the sensor location; Fig. 8(c) shows that the amplitude of the vibration was reduced from about 2V to about 0.45V, which represents about 77.5% reduction of the beam vibration at the sensor location; Fig. 8(d) shows that the amplitude of the vibration was reduced from about 1.8V (peak to peak) to about 0.32V, which represents about 82.2% reduction of the beam vibration at the sensor location; Fig. 8(e) shows that the amplitude of the vibration was reduced from about 0.65V (peak to peak) to about 0.13V, which represents about 80% reduction of the beam vibration at the sensor location.



(a)



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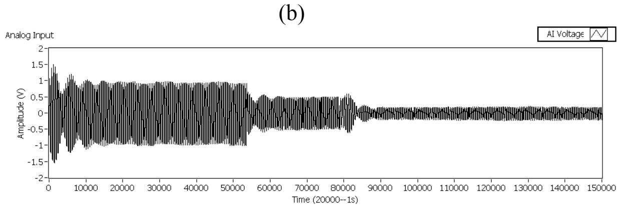
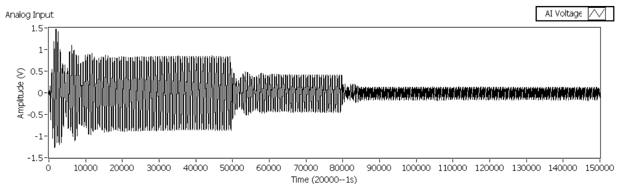
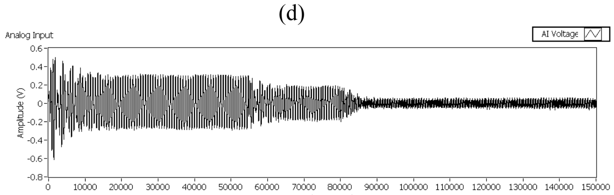


(c)



(d)



(e)

Fig. 8: Beam vibration reduction examples

For the same primary noisy sinusoidal signal as in the above five examples, without reducing the first calculated control signal amplitude, the system can get almost the same vibration amplitude reduction right after the first control signal. These examples show the online adaptive ability of the system. In some other experiments, the system was tried to repeat the vibration detection and control loop in 25 ms and worked very well.

Experimental results have also showed that the designed AVC system eliminates the sensitivity to time delays. Some experiments have been executed by changing the position of the control shaker or the point of interest, i.e., the sensor location, and therefore changing the time delays. After each modification, an initialization program can be run to collect training data and train the ANN model automatically based on the new experimental setup, and therefore absorbs the information of new time delays. After retraining, the AVC can work as well as before. For example, Fig. 8(a) shows a reduction of 82.7% in vibration amplitude when the primary vibration of the beam was at 32.33 Hz. After moving the sensor to another location (478 mm from the clamped end of the beam) and retraining the ANN, the AVC system can still get a reduction around 82%. The experimental outcomes did not show reduction of the AVC system ability caused by time delay changes.

Many Many papers, e.g., [6], have already demonstrated the ability of ANN control systems to deal with nonlinearity because of the nature of ANNs. Although the ANN used in the current work is not design for dealing with nonlinearity, the AVC system has proved to be able to deal with nonlinearity as long as the vibration frequency can be measured accurately. In the above experiments, as mentioned before, the primary shaker was simply pushed up against the beam to introduce nonlinearity into the experimental setup. By increasing the driving force of the primary disturbance, the primary shaker rattle as it loses the contact with the beam, and therefore will make the resultant error signal spectrum noisier. To check the ability of the AVC system in dealing with nonlinearity, some other experiments were completed with the primary shaker attaching to the beam. The results of these experiments are almost the same as the results shown above. In most cases, for the same inputs, the outcome differences of the two different setups are within 8%. For example, when the frequency of the primary signal is about 45.88Hz and the amplitude is about 0.27V, a reduction of 57.9% of the beam vibration at the sensor location was obtained when the primary shaker was simply pushed up against the beam; when the primary shaker was attached to the beam, for the same primary signal, the reduction was around 59%.

IV. Discussion

The experimental results show that the proposed AVC system works effectively. The ANN controller of the modified AVC system can reduce the root mean square (RMS) vibrations by up to 90%. The reductions in the RMS vibrations have a very significant effect on the fatigue life of a structure in practical application. Generally, reducing the RMS vibrations by just 10% doubles the fatigue life [7].

By using a real-time developing environment, in some experiments, the designed AVC system was tried to repeat the vibration detection and control loop in 25 ms and worked very well. It is online adaptable. The repetition of adding new control signals can be set up at any specific time during online control with finite number times. To repeat the vibration detection and control loop in infinite times is a part of future work.

The AVC system is also robust when the experimental setup changes. When the setup changes, the AVC system can collect training data and train the ANN model automatically via running a calibration program and then the system is prepared for AVC of the new setup.

At the present time, the AVC system has proved to be able to deal with noisy sinusoidal vibrations. Its ability to deal with more complicated signals will be tested in the future.

V. Conclusions

An effective, adaptable, and real-time online AVC system to suppress noisy sinusoidal vibrations of a cantilever beam has been achieved. The efficiency of this controller is shown through experimental verification. This AVC system could be used for machining chatter suppression because it is widely known that chatter signals have harmonic shapes, and their frequencies are around the respective natural frequencies of the machining systems. Moreover, some tools, e.g., a boring bar, can be modeled as some cantilever beams.

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